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Analysing the effect of partner characteristics on the performance of horizontal carrier collaborations

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Abstract In order to survive under the ever increasing pressure to operate more efficiently, transportation companies are obliged to adopt a collaborative focus. Although organisations become increasingly aware of the inevitable character of horizontal collaboration, surveys report failure rates up to 70 percent for starting strategic partnerships. While a growing body of research acknowledges the importance of fit between partners for coalition sustainability, no extensive study has been performed on the numerical relationship between specific company traits and the performance of the alliances these organisations are involved in. This paper empirically investigates the impact of coalition characteristics on attainable collaborative savings in a joint route planning context. Factorial analysis of variance is applied to examine desirable coalition structures for horizontal carrier collaborations based on request sharing. Overall, our experiments suggest that carriers may reap significant operational benefits from sharing orders. However, the extent of these benefits highly depends on the characteristics of the partnering organisations, stressing the importance of careful partner selection.

Keywords Horizontal collaboration; Partner characteristics; Joint route planning; Meta-heuristics; Experimental design

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1 Introduction

Severe competition in global markets, the introduction of products with shorter life cycles, rising petrol and labour prices, a growing body of transport legislation and heightened expectations of customers have caused profit margins of carriers to shrink (Cruijssen et al. 2007b). Traditionally, transportation organisations relied on their internal potential to reduce costs and increase profitability. Most companies, however, have exhausted the opportunity to improve through process optimisation. In order to survive under the ever increasing pressure to operate more efficiently, carriers are obliged to adopt a collaborative focus which opens up cost saving opportunities that are impossible to achieve with an internal company focus (Ergun et al. 2007; Wang and Kopfer 2011; Vanovermeire and Sörensen 2014). Since vertical cooperation in supply chains has been the focus of various research efforts over the last decades (e.g. Holguín-Veras et al 2008; Unnikrishnan et al 2009; Holguín-Veras et al 2011; Habis and Csercsik 2015), this paper extends the knowledge field on horizontal logistics cooperation. Horizontal logistics cooperation may be defined as collaboration between two or more firms that are active at the same level of the supply chain and perform comparable logistics functions (Cruijssen et al. 2007c). Through partnering with fellow transportation organisations, carriers may extend their resource portfolio, reinforce their market position, enhance their service levels and create a more efficient and environmentally friendly transport planning (Krajewska and Kopfer 2006; Caschili et al. 2014; Li et al. 2016; Lin et al. 2016; van Lier et al. 2016).

Although transport companies become increasingly aware of the inevitable character of collaboration, surveys report failure rates from 50 to 70 percent for starting partnerships (Schmoltzi and Wallenburg 2011). Because every partner of a horizontal cooperation still maintains its independency, the risk of opportunism remains real. Besides that, the success of achieving collaborative benefits strongly depends on the degree of fit between cooperation participants (Verstrepen et al. 2009; Martin et al. 2016). Similar or complementary strategic orientations, managerial practices, organisational characteristics and partnership goals could significantly influence collaborative performance (Parkhe 1993; Lambert et al. 1999). While a growing body of collaboration research acknowledges the importance of partner characteristics (Cruijssen et al. 2007a; Lozano et al. 2013; Guajardo and Rönnqvist 2015; Guajardo et al. 2016), no extensive study has been performed on the numerical relationship between specific company traits and the performance of the alliances these organisations are involved in. The main contribution of our paper is thus to provide practical recommendations on which partnership structures may provide the highest collaborative benefits.

Based on the literature review on collaborative logistics described in Verdonck et al. (2013), the influence of coalition characteristics will be investigated in an order sharing context. In the majority of carrier alliances customer orders from all participating carriers are combined and collected in a central pool and efficient route schemes are set up for all requests simultaneously using appropriate vehicle routing techniques, a collaboration

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approach that may be labelled joint route planning. In this way, scale economies, in terms of reduced travel distance, empty vehicle movements and number of required trucks, could be obtained by merging the distribution regions of all collaboration partners (Cruijssen and Salomon 2004; Cruijssen et al. 2007a). Since existing studies mainly focus on demonstrating the benefits associated with joint route planning, an empirical analysis of the influence of cooperation structure on partnership performance could provide useful insights for transportation companies considering collaboration.

An experimental design is set up to perform our numerical analyses. A factorial analysis of variance (ANOVA) provides insight into the effects and interactions between five coalition traits. In this context, the research work of Cruijssen et al. (2007a) and Palhazi Cuervo et al. (2016) is extended. As opposed to the more general impact analysis of coalition characteristics done by Cruijssen et al. (2007a), our goal is to define which specific partner traits may complement each other in a joint route planning setting. Moreover, while Palhazi Cuervo et al. (2016) aim to determine the most profitable coalition structures in a shipper environment, as opposed to our carrier perspective, their experiment is limited to the study of three company characteristics for coalitions of only two partners.

The main scientific contributions of this paper can be summarised as follows. First, as the existing research work on joint route planning mainly focuses on demonstrating its cost reduction potential, a mathematical vehicle routing formulation is developed. The collaborative carrier environment studied in this paper can be defined as a multi-depot pickup and delivery problem with time windows (MDPDPTW), a vehicle routing problem (VRP) that has only scarcely been researched (Montoya-Torres et al., 2015). Second, as proven by the recent increase in research on rich vehicle routing problems (Drexl 2012; Schmid et al. 2013; Caceres-Cruz et al. 2014; Lahyani et al. 2015), consideration of practical applications related to vehicle routing becomes relevant in today's complex environment. For this reason, the novelty of our paper lies in the application and empirical analysis of an existing routing problem in a practical real-world context with the aim of providing guidelines to practitioners. More specifically, the main contribution is to provide insight in the impact of coalition characteristics on the collaborative profit level of carrier alliances, using a well-known statistical research method. In this way, recommendations are made to transportation organisations considering collaboration on how they should tackle the partner selection process.

The remainder of this paper is organised as follows. First, the current research field of horizontal logistics cooperation in general and joint route planning specifically is summarised and the importance of partner fit in strategic alliances is discussed. Second, the joint route planning problem applicable in a carrier cooperation context is formally defined, together with the solution approach used to solve this VRP. Third, the research methodology is described and studied hypotheses are clarified. Fourth, results of a factorial ANOVA on the impact of coalition characteristics on collaborative performance are presented and discussed. Finally, conclusions and possible directions for future research are formulated.

2 Literature review

2.1 Joint route planning

Scientific research on horizontal carrier collaboration can be divided into two main research streams: order sharing and capacity sharing (Verdonck et al. 2013). The majority of carrier cooperation literature focuses on carrier alliances in which customer requests are exchanged between the participating organisations through various techniques (Verdonck et al. 2013). A mechanism which has been generally accepted in a horizontal carrier cooperation context is joint route planning. Joint route planning implies that customer orders from all alliance partners are combined and collected in a central pool and efficient route schemes are set up for all requests simultaneously (Cruijssen and Salomon 2004; Cruijssen et al. 2007a).

Cruijssen and Salomon (2004) consider a transport network with multiple carriers and customers. The purpose of the study is to compare transport costs of individual carriers with total transport costs in a system where orders are shared and a joint route planning is established. To solve the joint route planning problem, customer requests are combined over all carriers. Using a simulation study, the authors demonstrate that joint route planning may lead to reductions in transportation costs up to 15%. Similarly, Cruijssen et al. (2007a) define a framework based on the VRP with time windows (VRPTW) to determine the synergy value of horizontal carrier cooperation through joint route planning. An appropriate heuristic is constructed to solve the route minimisation problem. Case study results show that joint route planning between three frozen food distributors saves about 30% in distance travelled. Moreover, the authors examine the sensitivity of collaborative savings to various operational characteristics of the alliance (e.g. number of orders, average order size, etc.). Nadarajah and Bookbinder (2013) study horizontal carrier collaboration within urban regions. Computational experiments indicate distance savings up to 15% when collaborating at the entrance of the city and additional reductions in kilometres driven up to 15% when carriers are involved in intra-city collaboration. Pérez-Bernabeu et al. (2015) compare a cooperative route planning scenario with various non-cooperative scenarios, differing in geographical customer distribution, in terms of distance-based and environmental costs. Another variant of the traditional VRP used to model the collaborative carrier order sharing problem is the multi-depot pickup and delivery problem (MDPDP), as described in Krajewska et al. (2008) under time windows. The authors test their approach both on artificial instances and real-life data from a German freight forwarder. Dahl and Derigs (2011) examine the order sharing problem in a collaborative network of carriers performing express customer orders. Since these organisations operate in a highly dynamic environment in which at no point in time a fixed set of requests may be planned, the problem is solved from a dynamic perspective. Based on a simulation study using real data from 50 European express carriers, Dahl and Derigs (2011) demonstrate that cost reductions up to 13% may be achieved when applying joint route planning. Contrary to the previous articles considering the entire transport network for collaboration, Bailey et al. (2011) focus on order sharing opportunities for the backhaul routes of partnering companies. The authors investigate possible reductions in a carrier's empty backhauls by adding customer requests of alliance partners to its backhaul transport. Computational experiments reveal that freight collaboration may lead to backhaul cost savings between 13% and 28%. Similarly, Juan et al. (2014) discuss horizontal collaboration between transportation companies through backhaul strategies. The goal of the joint route planning is to minimise both distance and emission based costs of the partners' distribution activities. Numerical experiments demonstrate average reductions in distance and environmental costs of 16% and 24% respectively.

The existing research work described above mainly focuses on demonstrating the cost reduction potential of order sharing between transportation companies. Following this observation, a first contribution of our work is the development of a clear mathematical vehicle routing formulation for the joint route planning problem, as presented in Sect. 3.2. While the papers summarised above provide suggestions on the characteristics of the joint route planning problem, we develop a formal and comprehensive problem formulation associated with horizontally collaborating carriers and fitting in the general VRP framework.

2.2 The influence of collaboration characteristics

Selecting the right partners constitutes a crucial phase in the development of a horizontal collaboration (Martin et al. 2016). Moreover, the amount of attainable collaborative savings is influenced by the degree of fit between the collaboration participants (Lin and Hsieh 2012). According to Brouthers et al. (1995) cooperating with an unsuitable partner is more damaging to an organisation than not collaborating at all. Carriers also seem to be aware of the crucial importance of partner selection, as indicated in a survey by Cruijssen et al. (2007b).

Van Breedam et al. (2005) distinguish four key factors that should be considered when selecting possible collaboration partners: trust and engagement, operational fit, strategic fit and cultural fit. Trust refers to each company's conviction that the other partners will refrain from opportunistic behaviour. Engagement reflects the preparedness of each alliance partner to make a contribution to the collaboration, evoking a mutual sense of responsibility towards alliance success (Schmoltzi and Wallenburg 2012). This contribution might take various forms, including financial resources, knowledge or material assets. Trust and engagement are necessary, but insufficient conditions to build a horizontal partnership. Other focal points are the operational, strategic and cultural fit with a potential partner. Operational fit concerns organisational characteristics on a financial and operational level such as company size, proprietary structure and profitability. In order for strategic fit to be present, the organisational strategies of the partners need to be compatible and mutually strengthen each other. A final key factor in partner selection is cultural fit. Compatibility between organisational cultures is crucial when a stable collaboration is aspired. Lambert et al. (1999) and Audy et al. (2012) also underline the importance of taking the cultural component into account. Given the intangibility of the corporate culture, cultural fit may be hard to verify. Possible indicators are the degree of customer focus, level of environmental awareness, management style and company reputation. In line with these four factors, Schmoltzi and Wallenburg (2011) define six dimensions associated with the structure of the cooperation that may impact its performance. First, the contractual scope defines the formality of the cooperation project. Second, the organisational scope refers to the number of companies taking part in the alliance. Third, the functional scope is associated with the activity domains in which organisations join forces. A cooperation might be limited to non-core activities or may involve core business' operations. Fourth, the geographical scope is related to the markets that are covered by the alliance. Organisations may decide to cooperate with competitors serving the same customers to improve market strength or may extend their market coverage by partnering with competitors from different geographical areas. In line with this geographical dimension, the service scope defines the products or services offered by the collaboration, which may again be complementary or supplementary. Finally, the resource scope refers to the degree of resource overlaps between the cooperation participants. A distinction is made between overlaps in business activities, customer base and company size. As such the 'resource scope' defined by Schmoltzi and Wallenburg (2011) shows a degree of similarity with the 'operational fit' presented in Van Breedam et al. (2005). Based on the partner selection criteria discussed above in theoretical, qualitative collaboration literature, we investigate and statistically analyse the effect of five measurable coalition characteristics on alliance performance. In Sect. 4.1 the studied hypotheses are discussed in detail.

In summary, the second contribution of our work is to provide insight in the impact of coalition characteristics on the collaborative profit level of carrier alliances by determining the most profitable alliance structures in a joint route planning setting. We are the first to do this for horizontal collaborations between carriers. While the paper of Palhazi Cuervo et al. (2016) is most related to our work, they consider coalition structures in a shipper environment in which flexibility in terms of order delivery provides collaborative savings that are not achievable in a carrier context. Moreover, their experiment is limited to the study of three company characteristics for coalitions of only two partners, as opposed to our experimental design including two-, three-, four- and five-partner coalitions differing in terms of four characteristics.

3 Mathematical formulation and solution approach

3.1 Problem statement

The joint route planning problem of collaborating transport companies studied in this paper can be defined as follows. Carriers receive pickup and delivery requests from different types of customers. In a static context, it is assumed that customer demand is known and fixed at the start and no additional requests are acquired during the execution of already determined transport schedules. Each route has to satisfy coupling and precedence constraints, meaning that for each order, the origin must precede the destination and both locations need to be visited by the same vehicle. In addition, hard time windows are associated with each request. In a non-cooperative environment, the routing problem associated with each individual carrier, may be classified as a single depot PDPTW. The objective of the PDPTW is to identify an optimal set of routes for a fleet of vehicles to serve all customers without violating vehicle capacity, time windows, precedence and coupling constraints. The optimality characteristic coincides with an objective function that minimises total customer service time, distance travelled, number of used vehicles or a weighted combination of these goals (Mitrovíc-Miníc 1998; Li and Lim 2003; Krajewska et al. 2008; Parragh et al. 2008b; Ropke and Cordeau 2009).

If carriers cooperate horizontally, pooling all their customer orders together to achieve potential savings, additional constraints have to be added to the PDPTW in order to optimally solve the joint route planning problem. The most important modification that needs to be made, is the adoption of a multi-depot perspective. As requests from all carriers are considered simultaneously, vehicles may depart from multiple depots. The joint route planning problem may thus be defined as a multi-depot PDPTW with the general purpose of identifying optimal routes for all customer requests simultaneously. This set of routes minimises total cost, guarantees that all requests are served within their time windows, all vehicles return to their respective depots and vehicle capacities are never exceeded (Krajewska et al. 2008).

3.2 Mathematical problem formulation

The multi-depot VRPTW with pickup and delivery has only scarcely been researched (Montoya-Torres et al. 2015). As such, an appropriate MDPDPTW formulation is developed for the joint route planning problem based on the description provided by Krajewska et al. (2008) and combinations of PDPTW and MDPDP formulations proposed in current literature (Mitrovíc-Miníc 1998; Ropke and Pisinger 2006; Parragh et al. 2008b; Ropke and Cordeau 2009; Liu et al. 2010b; Sombuntham and Kachitvichyanukul 2010; Ben Alaïa et al. 2013).

The problem is defined over a directed graph $G = (N,A)$ with node set $N = \{I,Z\}$ and arc set A. The node set N can be divided into a set of customer nodes $I = \{P,D\}$ and a set of depot nodes Z, coinciding with the different cooperating carriers. The customer nodes, ranging from 1 to $2n$, consist of a set of pickup locations $P = \{1,...,n\}$ and a set of delivery locations $D = \{n+1,...,2n\}$. The depot nodes Z can be split up in nodes representing the start location of a vehicle $\{\tau_1,\ldots,\tau_m\}$ and nodes that correspond with the end station of a vehicle $\{\tau'_1,\ldots,\tau'_m\}$. K is the set of vehicles (with index $k = 1,\ldots,m$) with identical capacity C, located at one of the depots related to the collaborating carriers. Every vehicle needs to start and end its route at the same depot.

Each request submitted by a customer consists of a pickup node i and a delivery node $n+i$. The value q_i denotes the amount of demand (pickup) or supply (delivery) at these respective nodes. As such, pickup nodes are associated with a positive value (q_i), delivery nodes with a negative value ($|-q_{n+i}| = q_i$) and depots with a $q_\tau = 0$. A time window $[e_i, l_i]$ is defined to represent the earliest and latest time to start servicing node i and a service time s_i to cope with the duration of the pickup/delivery service at every node. Finally, to each arc $(i,j) \epsilon A$ a distance-dependent cost $c_{ij} \geq 0$ and a corresponding travel time $t_{ij} \geq 0$ can be assigned.

The decision variables determined during the static joint route planning problem are the following:

$$x_{ij}^k = \begin{cases} 1 \text{ if arc } (i, j) \text{ is traversed by vehicle } k, \\ 0 \text{ otherwise.} \end{cases}$$

Q_i^k = load of vehicle k when leaving node i

B_i^k = time at which vehicle k begins service at node i

Using these variables, the MDPDPTW can be formulated as the following mathematical model:

$$Min \sum_{k\in K} \sum_{i\in N} \sum_{j\in N} c_{ij} x_{ij}^k \qquad (1)$$

Subject to

$$\sum_{k\in K}\sum_{j\in N} x_{ij}^{k} = 1 \qquad \forall i \in P \qquad (2)$$
$$\sum_{j\in N} x_{ij}^{k} - \sum_{j\in N} x_{n+i,j}^{k} = 0 \qquad \forall\, i \in P, k \in K \qquad (3)$$
$$\sum_{j\in P\cup\{\tau_k'\}} x_{\tau_k,j}^{k} = 1 \qquad \forall k \in K \qquad (4)$$
$$\sum_{i\in D\cup\{\tau_k\}} x_{i,\tau_k'}^{k} = 1 \qquad \forall k \in K \qquad (5)$$
$$\sum_{j\in N} x_{ji}^{k} - \sum_{j\in N} x_{ij}^{k} = 0 \qquad \forall\, i \in N, k \in K \qquad (6)$$
$$B_i^k + t_{i,n+i} \le B_{n+i}^k \qquad \forall\, i \in P, k \in K \qquad (7)$$
$$B_j^k \ge (B_i^k + s_i + t_{ij})x_{ij}^k \qquad \forall\, i \in N, j \in N, k \in K \qquad (8)$$
$$Q_j^k \ge (Q_i^k + q_j)x_{ij}^k \qquad \forall\, i \in N, j \in N, k \in K \qquad (9)$$
$$e_i \le B_i^k \le l_i \qquad \forall\, i \in N, k \in K \qquad (10)$$
$$Q_i^k \le C \qquad \forall\, i \in P, k \in K \qquad (11)$$
$$Q_i^k \le C + q_i \qquad \forall\, i \in D, k \in K \qquad (12)$$
$$x_{ij}^k \in \{0, 1\} \qquad \forall\, i \in N, j \in N, k \in K \qquad (13)$$
$$B_i^k \ge 0 \qquad \forall\, i \in P \cup D, k \in K \qquad (14)$$
$$Q_i^k \ge q_i \qquad \forall\, i \in P, k \in K \qquad (15)$$
$$Q_i^k \ge 0 \qquad \forall\, i \in D, k \in K \qquad (16)$$

The objective function (1) minimises the sum of distance-dependent costs. Constraints (2) and (3) ensure that each customer request is served exactly once and that pickup and delivery nodes are visited by the same vehicle. Constraints (4) and (5) guarantee that the route of each vehicle k starts at its respective depot and returns there at the end of its route. Conservation of flow is expressed by equation (6). Constraints (7) ensure that delivery can occur only after pickup. Then, restrictions (8) and (9) make sure that consistency of time and load variables is ensured and eliminate the possibility of subtours. Constraints (10) guarantee that the solution of the problem does not violate the customer provided time windows. Constraints (11) and (12) ensure that vehicle capacity is not exceeded throughout the tours, for pickup and delivery orders respectively. Finally, statement (13) enforces the binary nature of some of the decision variables used in the model, while constraints (14), (15) and (16) impose non-negativity restrictions on the other decision variables.

Our problem formulation is nonlinear due to constraints (8) and (9). Equivalent with Cordeau (2006), we introduce constants M_{ij}^k and W_{ij}^k to linearise these constraints as follows:

$$B_j^k \ge B_i^k + s_i + t_{ij} - M_{ij}^k(1 - x_{ij}^k) \qquad \forall\, i \in N, j \in N, k \in K \quad (17)$$
$$Q_j^k \ge Q_i^k + q_j - W_{ij}^k\left(1 - x_{ij}^k\right) \qquad \forall\, i \in N, j \in N, k \in K \quad (18)$$

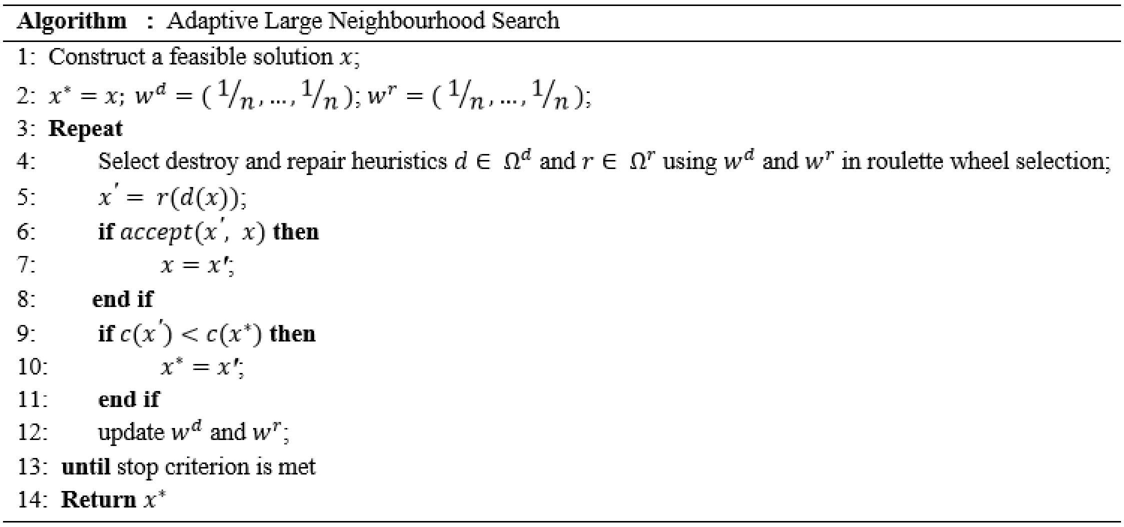
Setting $M_{ij}^k \ge \max\{0, l_i + s_i + t_{ij} - e_j\}$ and $W_{ij}^k \ge \min\,\{C, C + q_i\}$ guarantees validity of constraints (17) and (18) respectively.

3.3 Solution approach

The MDPDPTW is a generalisation of the classical VRP and thus belongs to the class of NP-hard problems. Because of its complexity, heuristics are needed to solve the joint route planning problem associated with the different coalition structures described in Sect. 2.2. Based on its high-quality performance for rich VRP problems (Parragh et al. 2008a), our solution procedure is based on the Adaptive Large Neighbourhood Search (ALNS) heuristic, originally developed by Ropke and Pisinger (2006) and generalised in Pisinger and Ropke (2007).

Regarding the solution procedure for the joint route planning problem, we want to state clearly that the goal of our research is not to propose a superior solution algorithm. On the contrary, the objective of our horizontal collaboration research is to present practical recommendations to logistics service providers in terms of desirable coalition structures and partner characteristics. As such, we make use of the widely applied ALNS procedure, which ensures good quality solutions in a reasonable time frame for interpretation purposes.

The ALNS heuristic, described below in pseudo-code (Figure 1), is based on the LNS heuristic proposed by Shaw (1998). In LNS, an initial solution is gradually improved by alternately destroying and repairing the solution. In this way, searching a large neighbourhood results in finding local optima of high quality and hence overall a LNS algorithm may return better solutions. The ALNS differs from the LNS in two important ways. First, the ALNS uses multiple removal and insertion heuristics during the same search, while LNS heuristics use only one method for removal and one for insertion. Selection of destruction and construction neighbourhoods is guided by a roulette wheel mechanism using statistics recording past performance of applied heuristics. Second, Pisinger and Ropke (2007) embed the search for high quality solutions in a simulated annealing meta-heuristic. While the original LNS only accepted solutions improving the goal function, ALNS also accepts gradually less deteriorating solutions.



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Algorithm : Adaptive Large Neighbourhood Search
Construct a feasible solution $x$;
$x^* = x$; $w^d = (1/n, \ldots, 1/n)$; $w^r = (1/n, \ldots, 1/n)$;
Repeat
    Select destroy and repair heuristics $d \in \Omega^d$ and $r \in \Omega^r$ using $w^d$ and $w^r$ in roulette wheel selection;
    $x' = r(d(x))$;
    if $accept(x', x)$ then
        $x = x'$;
    end if
    if $c(x') < c(x^*)$ then
        $x^* = x'$;
    end if
    update $w^d$ and $w^r$;
until stop criterion is met
Return $x^*$
```

Figure 1 Pseudo-code of ALNS

The specific algorithm components and implementation details of the ALNS meta-heuristic applied to solve our joint route planning problem are the following. First, as suggested by Pisinger and Ropke (2007), an initial feasible solution is generated using a regret-2 heuristic. Regret-*k* heuristics try to improve the short-sighted behaviour of greedy heuristics. For each request a regret value is calculated equal to the difference in cost between inserting the request in its best route and its *k*th-best route. Then, requests with the highest regret values are inserted first in the solution (Ropke and Pisinger 2006). Second, in order to destroy and repair solutions, five insertion (greedy sequential, greedy parallel, regret-2, regret-3 and regret-4) and five removal heuristics (random removal, worst removal, related removal, time-oriented removal and neighbour graph removal) are implemented. The greedy insertion heuristics repeatedly insert requests at their minimum cost positions, either sequentially (considering available routes one by one) or parallel (considering all routes simultaneously). The random removal heuristic removes *q* randomly selected requests from the solution, while the worst removal heuristic aims at removing requests associated with high solution costs. The related removal heuristic makes use of a relatedness measure based on the distance between two requests to remove customers. The time-oriented removal heuristic works in a similar way, but now relatedness between two requests is determined by their respective times of pickup and delivery. Neighbour graph removal decides on request removal based on the historical success of visiting two nodes immediately after each other in a route (Ropke and Pisinger 2006; Pisinger and Ropke 2007). For the purpose of diversifying the search, a noise parameter is added to the objective function of the insertion heuristics. In each iteration, the decision whether to use the ’original’ or ’noise’ heuristic is taken based on an adaptive mechanism keeping track of the past performance of the respective heuristics with and without noise. Third, different from the Pisinger and Ropke (2007) ALNS, deterministic, instead of simulated, annealing is chosen as the master local search framework. According to Dueck and Scheuer (1990), who introduced deterministic annealing (DA) or threshold accepting, the success of simulated annealing is sensitive to the choice of the annealing schedule. Moreover, DA offers greater simplicity but reaches similar good results in previous research (Bräysy et al. 2008; Caris and Janssens 2010). The difference between simulated and deterministic annealing lies in their different solution acceptance rules. Using DA, a neighbouring solution with a worse objective value than the current solution is accepted if the deterioration is less than a deterministic threshold value T. In comparison to simulated annealing, it is not required to compute acceptance probabilities. The algorithm threshold value T is gradually lowered until no more deteriorations are allowed. The DA applied in our ALNS is based on the implementation strategy of Bräysy et al. (2008) and Caris and Janssens (2010). Solution acceptance with DA can be described as follows. The threshold value T is initially set at a maximum value T_{max}. In each iteration without improvement in objective function value T is lowered with the reduction parameter ΔT. The threshold value is reset to $r * T_{max}$ whenever it reaches zero, with r representing a random number between zero and one. When after a predefined number of iterations no improvements have been found and T reaches zero again, the algorithm restarts from the current best solution found. The process is repeated for a predefined number of iterations.

In order to keep the parameter tuning in line with Krajewska et al. (2008), we have used almost the same parameter setting for our ALNS as determined in Ropke and Pisinger (2006), except for the simulated annealing related parameters which are now replaced by deterministic annealing parameters. The DA parameters were calibrated by selecting three values for each parameter based on preliminary computational experiments and testing all combinations on 24 instances, one for each alliance class considered in the experimental design (see Sect. 4.2). As such, the algorithm is restarted from the current best solution after 20 iterations without any improvements.

The maximum threshold value T_{max} equals 1.5, with a change in threshold value ΔT of 0.045. Analogue to Ropke and Pisinger (2006), the entire ALNS process is repeated for 25000 iterations.

4 Research methodology

To investigate the impact of specific coalition characteristics on attainable collaborative performance, the statistical approach of experimental design is used. The primary goal of an experimental design is to establish a causal relationship between the independent and dependent variables at hand. This relationship is statistically derived with the use of ANOVA by examining the value of the performance measure associated with various levels of the independent parameters or factors. Lozano et al. (2013) and Vanovermeire et al. (2013) have already demonstrated that this technique is suited to analyse the influence of different parameters in a horizontal shipper collaboration setting.

Based on the partner selection criteria discussed in Sect. 2.2, we investigate and statistically analyse the effect of five measurable coalition characteristics on alliance performance. In Sect. 4.1 the studied hypotheses are discussed in detail.

Since no test instances are available for the specific collaboration problem investigated here, the method used to generate artificial instances is described in subsection 4.2, together with a presentation of the experimental factors coinciding with the relevant cooperation characteristics. With regards to the impact analysis of coalition characteristics on collaborative performance, we focus exclusively on comparing distance-dependent cost results with and without joint route planning. The use of a single performance measure to compare benefits the clarity and comprehensibility of the insights provided to practitioners. Moreover, this choice is consistent with existing literature on the joint route planning problem, as discussed in Sect. 2.1.

4.1 Research hypotheses

In order to investigate the effect of specific coalition characteristics on alliance performance, we hypothesise the following five relationships based on theoretical, qualitative collaboration literature.

First, the influence of **the number of partners** (organisational scope) on cooperation performance is examined. In this way, it can be determined whether it is better to share orders with a large or a limited number of fellow transportation companies. The statements made by Park and Russo (1996), Griffith et al. (1998) and Lozano et al. (2013) lead to the following hypothesis:

> *H_1: The number of collaborating partners has a positive impact on coalition performance.*

Second, in line with the operational fit concept described by Van Breedam et al. (2005), the impact of similarity in **size of the collaborating companies** is studied. Size of a carrier is measured in terms of the amount of customer requests it initially needs to serve before the cooperation. The question to be answered here is whether a carrier is better off cooperating with equally sized organisations or if more savings may be achieved in an alliance consisting of companies differing in size. In accordance with experimental results of Cruijssen et al. (2007a) and Vanovermeire et al. (2013), the following hypothesis is investigated:

> *H_2: Coalition performance is higher for cooperations established between equally sized carriers compared to collaborations between organisations differing in size.*

Third, the effect of resource overlaps between alliance partners, as discussed by Schmoltzi and Wallenburg (2011), is analysed in three ways. The resource scope is first defined as the **degree of overlapping geographical coverage** between cooperating carriers, leading to our third hypothesis:

> *H_3: Coalition performance is higher for cooperations established between carriers operating within the same geographical area compared to collaborations between companies active in completely unrelated customer markets.*

Next, the effect of equalities and differences in customer base characteristics is investigated. This concept is translated in two partner characteristics. On the one hand, the impact of overlap between cooperation participants in terms of **customer order time windows** is studied:

H_4: Coalition performance is higher for cooperations formed by partners with different order time windows compared to collaborations established between carriers serving orders with equal time windows.

On the other hand, the effect of similarities and differences in **average order size** of partners is investigated:

H_5: Coalition performance is higher for cooperations formed by partners with different order sizes compared to collaborations established between carriers serving orders of similar size.

4.2 Generation of test instances and alliance structures

To investigate the impact of different alliance characteristics on coalition performance, total costs are compared for carriers operating independently and carriers participating in a horizontal alliance with varying structures. Considered here are horizontal collaborations with a long-term horizon between a limited number of transport organisations. The dependent variable of our experimental design can be defined as:

$$\text{Coalition performance (CP)} = \sum_{i=1,\dots,N} c(i) - c(N) \qquad \forall\ i\ \in N$$

with N denoting the total number of coalition partners, $c(i)$ the stand-alone distance-dependent costs of the individual companies and $c(N)$ the total distance-dependent cost of the coalition. All relevant distance-dependent costs are determined using the ALNS described in Sect. 3.3.

First, test instances are created for individual carriers differing in terms of the partner characteristics presented in Sect. 4.1. Table 1 provides an overview of the characteristics associated with these individual carrier instances together with their implementation details. Regarding the chosen implementation values, experienced practitioners were consulted in order to create realistic partnership structures fitting in a joint route planning setting. Second, the individual carrier instances are combined in a factorial experiment to represent horizontal alliances with varying structures.

Considering the individual carrier instances (Table 1), organisations of three different sizes are created. 'Small' carriers have to serve between 15 and 25 customer requests, 'medium' carriers are responsible for 60 to 70 customer orders and 'large' carriers are assigned 100 to 120 requests. This implementation is in line with the European logistics environment comprised of a significant amount of SME's (small and medium-sized enterprises). To examine the impact of resource overlaps between alliance partners, within each of the three carrier categories just described, distinct carrier profiles are created. First, the Li and Lim (2003) distinction between LR (randomly distributed customers) and LC (clustered customers) instances is used to cope with the geographical coverage associated with individual carriers. Second, a distinction is made between carriers serving customers with broad time windows and carriers performing orders with narrow time windows. The average time window width of customer orders characterised by 'broad' time windows is two to three times larger than that of orders with 'narrow' time windows. Third, carrier instances may differ in terms of the average size of the orders that need to be served. A 'small' order takes up 5% to 15% of vehicle capacity, while a 'large' order occupies 30% to 40% of vehicle space. Transported goods and used vehicles are considered to have homogeneous characteristics among participating transport organisations.

Table 1 Characteristics of individual carrier instances

Characteristic	Categories	Implementation
Carrier size	Small	$U(15, 25)$ orders per carrier
	Medium	$U(60, 70)$ orders per carrier
	Large	$U(100, 120)$ orders per carrier
Geographical coverage	R	Customer locations: random
	C	Customer locations: clustered
Order time windows	1	Narrow order time windows
	2	Broad order time windows
Order size	Small	Order size: $U(0.05, 0.15)$ * vehicle capacity
	Large	Order size: $U(0.30, 0.40)$ * vehicle capacity

The five experimental factors and their associated factor levels are listed in Table 2. Horizontal carrier alliances with different coalition characteristics are generated by combining the individual carrier instances as follows. Regarding the number of partners in a coalition, two-carrier, three-carrier, four-carrier and five-carrier partnerships are considered. By incorporating this 'coalition size' factor into the experimental design, the statement made by Lozano et al. (2013) that there exists a limit above which the synergy increase generated by adding another company to the collaboration is negligible, could be accounted for. Next, due to the stated importance of operational fit between coalition partners (e.g. Van Breedam et al., 2005), a distinction is made between alliances consisting of equally sized organisations and alliances comprised of companies differing in size for each of the studied coalition sizes. As such, 'equal size' coalitions are established either between small carriers, medium-sized carriers or large carriers. In order to get a balanced experimental design, for the 'different size' coalitions a random selection is made of three coalition structures containing a mix of small, medium and large carriers. As a consequence, our experimental design can be considered fractional instead of full since not all factor level combinations are included. The motivation behind this approach is to reduce the size of the experiment in order to be able to solve it within a reasonable computation time. Including all carrier size combinations for the three-partner coalitions only would already increase the number of test instances by 192, for example. Within each of these 24 alliance classes, coalitions are then created between carriers operating in the same geographical area (combination of LR instances) and carriers serving customers in different regions (combination of LC instances). By joining instances comprised of customers that are randomly dispersed within the same area, savings can be calculated for cooperations established between carriers who have a strong overlap in geographical scope. On the contrary, collaborations between companies active in unrelated customer markets could be quantified by combining instances in which carriers serve customers located in unrelated clusters. For clarification purposes, both cooperation structures are visualised in Figure 2. In addition, a distinction is made between coalitions established between carriers who are similar in terms of average order time windows (combination of all ‘narrow time windows’ or all ‘broad time windows’ instances, each representing half of the number of instances) and carriers responsible for customers with different time window widths (mix of ‘narrow time windows’ and ‘broad time windows’ instances, divided equally within every instance). The total time horizon, the time period between the earliest time window start and latest time window end, of all developed instances remains within the same range (on average 2500 time units). In order to avoid the positive effect of broad time windows on performance (Li and Lim, 2003) interfering with the effect analysis performed in this paper, no separate instances have been created for the “1” and “2” carrier categories of Table 1. Finally, both alliance structures with only small or large average order sizes and coalitions servicing a mix of small and large orders are created. For comparison and analysis purposes, three instances are generated for each of the described coalition profiles, leading to a total of 1152 test instances.

We acknowledge the limitations of the experimental study presented in this paper. The consideration of a fractional design may influence the general validity of the findings. The conclusions, however, underline the value of carefully selecting coalition partners and provide recommendations on which partnership structures may provide higher collaborative benefits.

Table 2 Experimental factors and factor levels

Factors	Factor levels (number of levels)
Number of partners	Two, three, four, five (4)
Carrier size	Small, medium, large, mix$_1$, mix$_2$, mix$_3$ (6)
Geographical coverage	Random, clustered (2)
Order time windows	Equal, mix (2)
Order size	Small, large, mix$_1$, mix$_2$ (4)

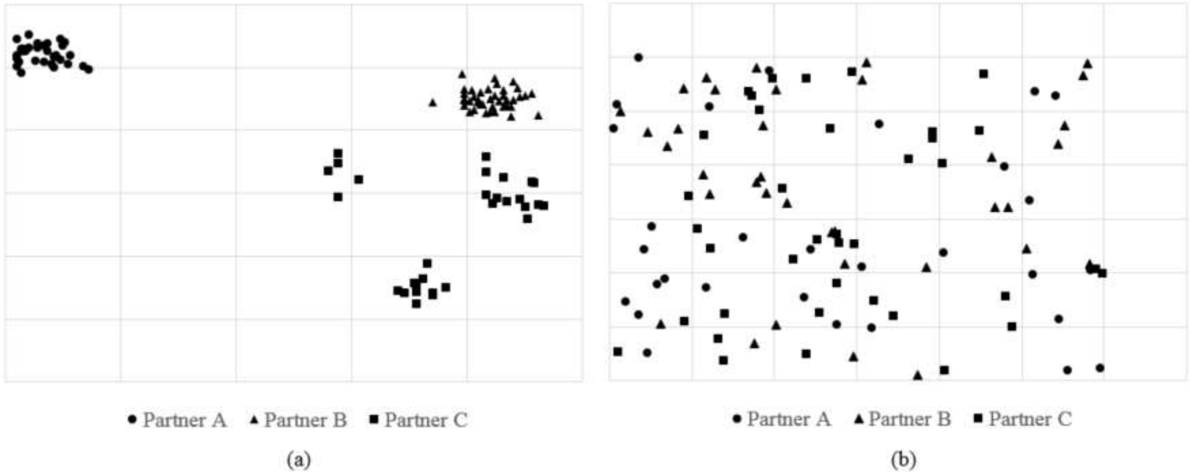

Figure 2 Geographical customer locations for a three-partner (a) ‘Clustered’ and (b) ‘Random’ coalition instance

5 Results and discussion

This section is devoted to the presentation and discussion of the joint route planning outcomes for different cooperation structures resulting from our fractional experimental design. The results of the experimental design are analysed by factorial ANOVA using SPSS for Windows Release 22.0. All tests are carried out on a Xeon CPU at 2.8 GHz with 64GB of RAM.

Coalition performance of all considered cooperation structures was determined using the ALNS with DA (see Sect. 3.3), implemented in Python. We briefly evaluate the performance of our meta-heuristic in Sect 5.1. Again, we want to stress that the goal of our research is not to propose a superior solution algorithm for the MDPDPTW. On the contrary, the objective of our horizontal collaboration research is to present practical recommendations or guidelines to logistics service providers in terms of desirable coalition structures or partner characteristics. For this reason, Sect. 5.2 discusses the main effects of the five experimental factors under study. By answering the hypotheses described in Sect. 4.1, we are able to determine which coalition characteristics have the most profound impact on collaborative performance. Sect. 5.3 describes a selected set of interaction effects to increase the explanatory power of our analysis. Finally, Sect. 5.4 summarises the managerial recommendations that can be made to practitioners based on our experimental analyses.

5.1 Algorithm performance

Before investigating the effect of different cooperation structures on collaborative savings, we evaluate the performance of our ALNS with DA, described in detail in Sect. 3.3. Running times of the algorithm are not discussed. The reason for this is that the meta-heuristic has been implemented in Python. Python-based programs tend to execute slower than other compiled programs (e.g. in C), but this interpreted language allows for rapid development of object-oriented programs especially suitable to examine algorithm potential.

Since the joint route planning problem presented here is most closely related to the description provided in Krajewska et al. (2008), we have used their computational results as a benchmark to validate the quality of our meta-heuristic against the original ALNS developed by Ropke and Pisinger (2006). After contacting the authors and receiving a selection of 35 instances belonging to T1, T2 and T3, a comparison was made between their collaborative cost results as presented in Krajewska et al. (2008) and those produced by our ALNS with DA for the same instances. Results reveal that our meta-heuristic performs equally well compared to the original ALNS. ALNS with DA results for T1, T2 and T3 instances display an average gap of 0.09% in terms of objective function value in comparison to the results of Krajewska et al. (2008).

5.2 Main effects of coalition characteristics on collaborative performance

The savings level associated with joint route planning ranges from 1,64% to 38,57% over all experiments, with an average savings level of 17,14%. Horizontal collaboration through order sharing can hence produce large operational benefits to carriers. However, because of the wide spread in possible savings, and because 1,64% may not be a sufficient gain to compensate for additional overheads of collaboration, a further investigation of the main effects of the five factors on the savings attained by the collaboration is in order.

Table 3 presents the ANOVA results for the main effects of the considered alliance characteristics on coalition performance. For each of the studied characteristics the ω^2 value (Olejnik and Algina 2000) is also reported, indicating their respective effect size. The mean coalition performance for the studied factor levels are displayed in Tables 4 and 5. Bonferroni and Games-Howell post hoc *t*-tests were used to define the statistical significance of the different factor levels (Field 2013).

The assumptions under which the ANOVA *F* statistic is accurate and reliable are independence of observations, homogeneity of variance and normally distributed observations. First, since all coalition instances are created by combining randomly generated carrier instances, observations may be considered independent. Second, regarding the homoscedasticity assumption, Levene's test has been applied, which tests the null hypothesis that the variances of the groups are equal. In case of violations of the homogeneity assumption, Welch's F is used to decide on the significance of factor effects (Field, 2013). Third, since the sample size is considerably large, we assume that the Central Limit Theorem is applicable which states that the distribution of the sample means approaches normality.

Table 3 Fractional ANOVA on coalition performance: Main effects

	SS	df	MS	F	p	ω^2
Number of partners	14428828902,876	3	4809609634,292	120,002	0,0000*	0,242
Carrier size	12133112998,734	3	4044370999,578	97,262	0,0000*	0,281
Geographical coverage	3102055233,864	1	3102055233,864	61,825	0,0000*	0,052
Order time windows	354122195,226	1	354122195,226	6,727	0,0096*	0,005
Order size	1628977171,835	2	814488585,918	18,608	0,0000*	0,039
Note: * Significant at α of	0,01					

Table 4 Mean coalition performance (CP) associated with studied factor levels (1/2)

Number of coalition partners	Mean CP	Carrier size	Mean CP	Geographical coverage	Mean CP
2	3892,209	Small	3187,501	Random	10725,294
3	7232,228	Medium	9015,907	Clustered	7390,856
4	10950,386	Large	14797,365		
5	13511,741	Mix	8882,020		

Table 5 Mean coalition performance (CP) associated with studied factor levels (2/2)

Order time windows	Mean CP	Order Size	Mean CP
Equal	8494,768	Small	8243,017
Mix	9621,381	Large	6890,533
		Mix	10233,673

Table 3 indicates that all of the main effects exhibit a statistical significance of less than 0,01. As such, each of the five studied coalition characteristics has a significant impact on coalition performance. The next subsections will discuss the experimental factors and the proposed hypotheses (Sect. 4.1) independently.

5.2.1 Number of partners (H_1)

H_1, which states that the number of partners in a collaboration influences its performance in a positive way, can be confirmed in a joint route planning context. Increasing the coalition size from two to five partners leads to a more than tripled profit level. However, companies need to be aware that coalition size cannot be enlarged infinitely. Collaborating with a large number of partners also increases alliance complexity and may dilute the strength of mutual partner relationships. In this context, Lozano et al. (2013) proof that there exists a limit above which the synergy increase generated by adding another company to the collaboration is negligible.

5.2.2 Carrier size (H_2)

Reviewing the ω^2 values reveals that the size of the carriers involved in the coalition has the most profound impact on its performance. In accordance with experimental results of Cruijssen et al. (2007a) and Vanovermeire et al. (2013), coalitions with the largest profits are achieved when a lot of orders are combined. The larger the pool of joint orders, the larger the potential to find a more profitable route plan for the collaboration. H_2 thus needs to be expounded upon in the joint route planning setting under study in this paper. While large transport organisations best seek for partners that are equal in size, small companies best join forces with a significant amount of equal-sized organisations and/or attract a large partner in order to enjoy savings levels associated with large order pools.

5.2.3 Geographical coverage (H_3)

Results demonstrate that coalitions between partners operating within the same geographical service area gain on average 45% more compared to collaborations between companies active in completely unrelated customer markets, confirming H_3. Increased geographical coverage may provide more cooperation opportunities and could thus lead to larger cost reductions. Overlapping customer markets seem to constitute an important aspect of coalition sustainability, as was also stated by Van Breedam et al. (2005), Cruijssen et al. (2007a), Schmoltzi and Wallenburg (2011) and Guajardo and Rönnqvist (2015).

5.2.4 Order time windows (H_4)

Table 5 suggests that differences in order time windows complement each other and may increase the number of possible improvement opportunities for the joint route plan. This confirmation of H_4 is supported by Schmoltzi and Wallenburg (2011) who found that, in practice, the majority of multi-lateral horizontal cooperations between logistics service providers are characterised by complementary customer portfolios of partners. However, the remark needs to be made here that, although the main effect of the time window width is significant, its explaining power is rather limited as shown by its low ω^2 value.

5.2.5 Order size (H_5)

In line with H_5, transport organisations involved in joint route planning best seek for partners that serve requests differing in size. A company with large orders may experience difficulties combining them in a single trip. As such, small orders can be useful to fill the remaining vehicle capacity. Moreover, organisations with small orders could avoid performing a multitude of routes, possibly with many detours, to deliver all its orders by combining them with larger ones. Following these statements, coalitions formed by partners with differing order sizes may achieve on average 26% more compared to collaborations established between carriers serving orders of similar size. Similar results were found by Vanovermeire et al. (2013) and Palhazi Cuervo et al. (2016) for two-partner shipper coalitions.

5.3 Interaction effects of selected coalition characteristics

Since the ω^2 values of the experimental factors 'number of partners' and 'carrier size' are prominently larger than the other ones, we investigate whether either of these two factors show a significant two-way interaction effect with one or more of the other collaboration characteristics, as presented in Table 6. In this way, possible dependencies between the number of coalition partners and their respective characteristics on the one hand and between the number of joint orders and their respective characteristics on the other hand are defined.

Table 6 Fractional ANOVA on coalition performance: Interaction effects

	SS	df	MS	F	p
Number of partners x carrier size	1185221477,536	9	131691275,282	4,649	0,0000*
Number of partners x geographical coverage	400973975,977	3	133657991,992	3,606	0,0130*
Number of partners x order time windows	177230740,989	3	59076913,663	1,486	0,2166
Number of partners x order size	351925332,179	6	58654222,030	1,822	0,0920
Carrier size x geographical coverage	338079621,970	2	169039810,985	4,576	0,0107*
Carrier size x order time windows	91224438,759	2	45612219,379	1,114	0,3291
Carrier size x order size	595458083,763	4	148864520,941	4,823	0,0008*

Note: * Significant at α of 0,05

ANOVA results demonstrate that the positive main effect of the coalition size is significantly influenced by the number of orders the partnering companies need to serve. As Figure 3 visualises, when more partners collaborate, a high number of joint orders implies that the number of kilometres driven could be reduced to a greater extent which thus leads to a higher profit level. The positive effects of coalition and carrier size thus significantly enforce each other in a joint route planning context. As such, large transport organisations considering horizontal collaboration best seek for multiple partners that are equal in size. Moreover, small carriers best join forces with a significant amount of equal-sized organisations or collaborate with large partners in order to enjoy saving levels associated with large order pools.

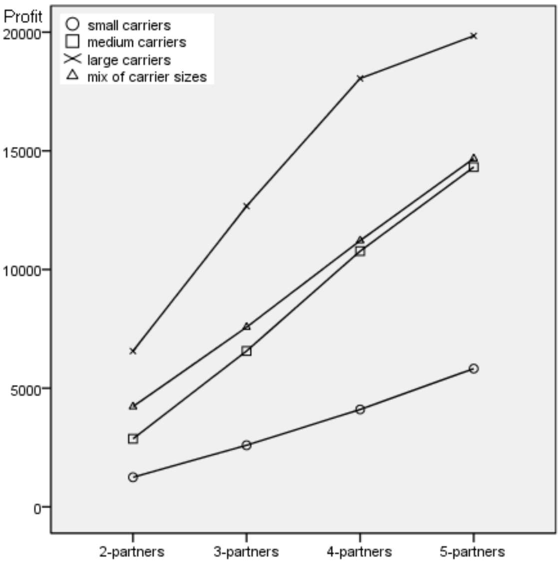

Figure 3 Average profit level for each combination of number of partners and carrier size

Next, Figure 4 demonstrates how the positive effect of increased geographical coverage has the most profound profit impact when coalition size grows. Given the complementarity of the geographical area that is served by the partnering companies, the larger the service region of the coalition, the more possibilities for efficient order sharing there are. Moreover, when the supply areas of the companies overlap each other the average transportation distances decrease (Guajardo and Rönnqvist 2015). Figure 5 confirms the importance of broad geographical coverage for alliance sustainability. As more orders are joined when large carriers cooperate, overlapping service regions provide more opportunities for collaborative synergy.

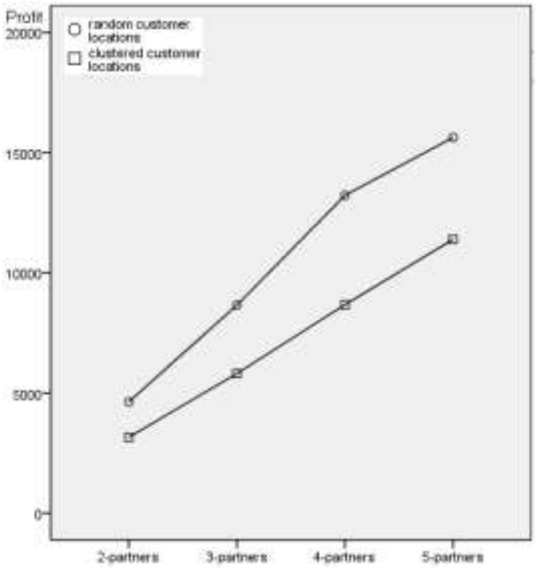

Figure 4 Average profit level for each combination of number of partners and geographical coverage

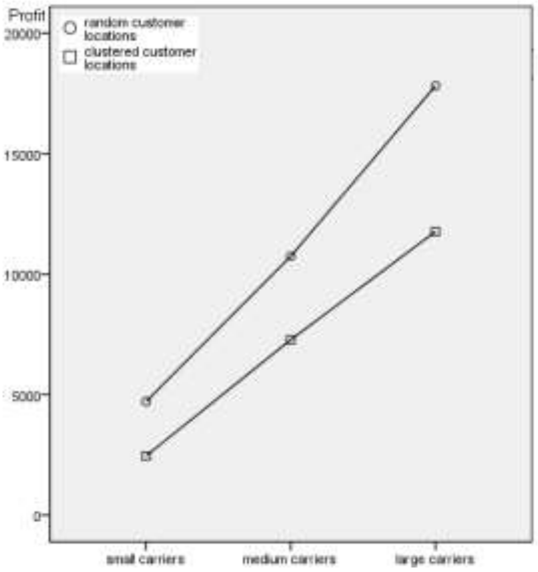

Figure 5 Average profit level for each combination of carrier size and geographical coverage

Finally, Figure 6 visualises the significant interaction effect between the partners' number of orders and their average order size. As already mentioned, coalitions with large profits are achieved when a lot of orders are combined. In order to enjoy even higher collaborative savings, it is best that large carriers seek companies of similar size, but with different order sizes in order to take full advantage of unused vehicle capacity. Similar to conclusions drawn by Vanovermeire et al. (2013) and Palhazi Cuervo et al. (2016) for two-partner shipper coalitions, the positive effects of number of orders and different order sizes significantly enforce each other in a joint route planning context.

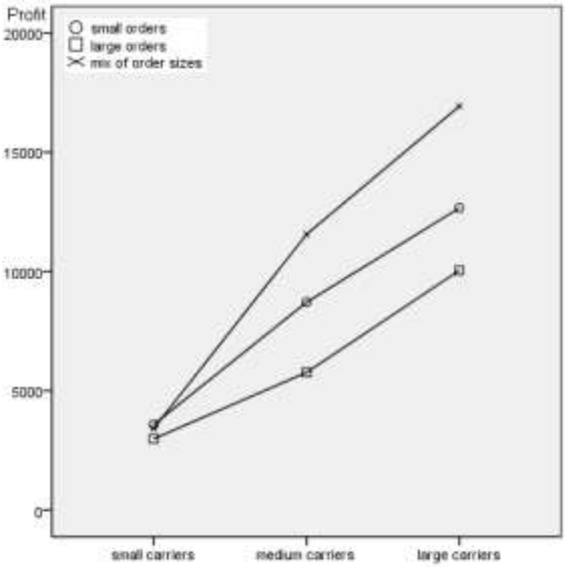

Figure 6 Average profit level for each combination of carrier size and order size

5.4 Managerial insights

Overall, our experiments suggest that carriers may reap significant operational benefits from sharing orders. However, the extent of these benefits highly depends on the characteristics of the partnering organisations, stressing the importance of careful partner selection. In terms of practical recommendations on collaborative performance, the most profitable coalitions consist of a sufficiently large amount of transport companies pooling a large number of orders that differ in size. In addition, the larger the service region of the coalition, the more possibilities for efficient order sharing there are.

6 Conclusions and future work

Although transportation companies become increasingly aware of the inevitable character of horizontal collaboration, surveys report failure rates up to 70 percent for starting strategic partnerships (Schmoltzi and Wallenburg 2011). While a growing body of collaboration research acknowledges the importance of partner characteristics (Cruijssen et al. 2007a; Lozano et al. 2013; Guajardo and Rönnqvist 2015; Guajardo et al. 2016), no extensive study has been performed on the numerical relationship between specific company traits and the performance of the alliances these organisations are involved in. The main contribution of our paper is thus to provide practical recommendations on which partnership structures may provide the highest collaborative benefits by means of analysing the results of an extensive experimental design.

Based on a review of existing scientific research on horizontal carrier collaboration, we empirically investigate the assumed impact of coalition characteristics on attainable collaborative savings in a joint route planning context. Joint route planning implies that customer orders from all alliance partners are combined and collected in a central pool and efficient route schemes are set up for all requests simultaneously using appropriate vehicle routing techniques. The routing problem associated with horizontally cooperating carriers may be classified and mathematically formulated as a MDPDPTW. Due to the complexity of the MDPDPTW, a meta-heuristic method based on ALNS and deterministic annealing has been applied to solve large problem instances.

The scientific contributions of this paper can be summarised as follows. First, as the existing research work on joint route planning mainly focuses on demonstrating its cost reduction potential, a mathematical vehicle routing formulation is developed. The collaborative carrier environment studied in this paper can be defined as a multi-depot pickup and delivery problem with time windows, a VRP that has only scarcely been researched. Second, as proven by the recent increase in research on rich vehicle routing problems (Drexl 2012; Schmid et al. 2013; Caceres-Cruz et al. 2014; Lahyani et al. 2015), consideration of practical constraints and applications related to vehicle routing becomes relevant in today's complex environment. For this reason, the novelty of our paper lies in the application and analysis of an existing routing problem in a practical real-world context with the aim of providing guidelines to practitioners. More specifically, the main contribution is to provide insight in the impact of coalition characteristics on the collaborative profit level of carrier alliances, using a well-known statistical research method. While we acknowledge the limitations of the experimental study presented in this paper, our conclusions underline the value of careful partner selection.

Based on extensive numerical experiments analysing the influence of alliance characteristics on the amount of attainable collaborative savings using factorial ANOVA, the following managerial insights may be formulated. First, results reveal that coalitions with the largest profits are achieved when a lot of orders are combined. The larger the pool of joint orders, the larger the potential to find a more profitable route plan for the collaboration. While large transport organisations best seek for partners that are equal in size, small companies best join forces with a significant amount of equal-sized organisations and/or attract a large partner in order to enjoy savings levels associated with large order pools. Second, considering the positive influence of the number of partners on collaborative performance, the importance of the total number of orders is confirmed. However, companies need to be aware that coalition size cannot be enlarged infinitely. Collaborating with a large number of partners also increases alliance complexity and may dilute the strength of mutual partner relationships. Third, broad geographic coverage and/or overlapping customer markets seem to constitute an important aspect of coalition sustainability. The larger the service region of the coalition, the more possibilities for efficient order sharing there are. Moreover, when the supply areas of the companies overlap each other the average transportation distances decrease. Finally, transport organisations involved in joint route planning best seek for partners that serve requests differing in size. In this way, the coalition can take full advantage of unused vehicle capacity.

To conclude, the following relevant suggestions for further research can be made. First, when exploring joint route planning, the focus may be expanded from considering cost minimisation exclusively to account for customer service effects. Besides its impact on cost and efficiency levels, cooperation with fellow transportation companies may also have an influence on the service that can be provided by each participating carrier. Although the offered service in terms of lead-time may improve for some of the cooperating partners, it may decline for others as a consequence of sharing customer orders. Second, in line with the two research streams defined by Verdonck et al. (2013), a similar impact analysis of cooperation characteristics on potential collaborative profit could be done in a capacity sharing context. Instead of exchanging customer requests, carriers may also cooperate horizontally through the joint use of vehicle capacity. Since owning a transportation vehicle involves a considerable capital investment and low capacity utilisation reduces a company's efficiency, logistics service providers may also share capacity and its associated costs (Agarwal and Ergun 2010). Capacity sharing provides a suitable alternative for order sharing, especially in environments where private order information cannot be communicated between alliance partners. Finally, the focus of this paper was on analysing the influence of cooperation structure on collaborative performance. The question remains however how to allocate these savings to the coalition partners. To ensure long-term stability of a horizontal logistics cooperation, positive incentives for the partners should be generated in the collaboration process. Since efficiency and effectiveness of allocation mechanisms are highly dependent on the characteristics of the respective coalition, future research work will investigate the impact of coalition structure on the performance of different cost or profit sharing mechanisms (Vanovermeire et al. 2014; Roson and Hubert 2015; Verdonck et al. 2016). In this way, practical recommendations may be formulated as to which allocation mechanisms are suitable in a joint route planning setting.

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